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CAPABILITY ACCUMULATION AND PRODUCT INNOVATION: AN AGENT-BASED PERSPECTIVE*

WORKING PAPER

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ABSTRACT

The paper studies the relevance of product heterogeneity for innovation dynamics using an agent-based model. The vantage point is a short a review on the empirical relevance of capability accumulation for innovation processes and an assessment of how these processes are modelled theoretically in evolutionary micro and macroeconomic models. This shows that the macroeconomic literature so far has focused on process innovations. To facilitate the consideration of empirical and microeconomic insights on product innovation in macroeconomic models, a simple agent-based model, which may later serve as an innovation module in macroeconomic models, is introduced.

Following up on recent empirical results, products in the model are heterogeneous in terms of their complexity and differ in their relatedness to each other. The model is used to study theoretical implications of different topological structures underlying product relatedness by conducting simulations with different 'product spaces'. The analysis suggests that the topological structure of the product space, the assumed relationship between product complexity and centrality as well as the relevance of product complexity in price setting dynamics have significant but nontrivial implications and deserve further attention in evolutionary macroeconomics. To this end, the model presented here may serve as a first step towards a module to be integrated in such a more comprehensive model framework.

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1 Introduction

The accumulation of productive capabilities has been found to be an important driver both for the successful development of individual firms (e.g. Aharonson and Schilling, 2016) as well as for the development of national economies (e.g. Hidalgo and Hausmann, 2009). Such accumulation is not only manifested via increases in the productivity of an existing set of products (*process* innovation), but also in the invention of new products and product varieties (*product* innovation).

The empirical literature on the accumulation of productive capabilities is considerable and has identified a number of stylised facts, both on the firm and aggregate level.[3] On the theoretical side models on the microeconomic level have been exceptionally successful in formalising the idea of product innovation, which has been shown to take place in a path dependent fashion since new inventions are a creative recombination of existing ideas (e.g. Caiani, 2017), and where collaboration among firms (e.g. Savin and Egbetokun, 2016), human capital accumulation and the engagement in R&D activities (e.g. Pyka et al, 2018) matter as important drivers of capability accumulation. In the evolutionary macroeconomic literature, the focus so far been much more on understanding process innovation: the most common way to account for innovation in evolutionary macroeconomic models is to allow firms to invest into R&D, which, if successful, results in an increase of productivity of that firm (see, e.g., Dawid and Delli Gatti, 2018; Aistleitner et al, 2020). With the exception of few cases, such as Ciarli et al (2018), product innovation has largely remained undiscussed. Given the greater challenge that the modelling of product innovation represents, the current state is understandable. Yet, it also warrants improvements given that the empirical literature suggests that product invention is a crucial mechanism underlying economic development (see, e.g., Hausmann et al, 2007; Hidalgo et al, 2007; Hidalgo and Hausmann, 2009).

Against this backdrop, the present paper aspires to make two contributions to the existing literature: first, it is meant as a first step in bridging the – thus far complementary – results of micro- and macroeconomics models: it takes up ideas developed in the microeconomic context, such as the invention of new products on a technology space, and formulates them in a manner that is not only more consistent with how innovation processes are considered in macroeconomic models, but also so simple that the model could be used as a module within a more comprehensive macroeconomic model. This could allow for the exploration of interaction effects between the mechanisms studied so far in an exclusively micro or macroeconomic framework.

Second, and related to the first aim, the paper takes up important empirical results and explores their theoretical implications for innovation processes in a microeconomic setting. More precisely, focusing on product innovation, we study how different structures of product relatedness affect the innovation activities of firms. In most of the existing literature, innovation processes do not follow a particular structure, yet the empirical literature has shown that products are related to each other in a systematic way, and that the structure of these relationships matter (Hidalgo et al, 2007).

To achieve the goals, the paper proceeds as follows: the next section substantiates the motivation of the paper and reviews the relevant literature. Section 3 introduces the model, the results of which are described in section 4. A discussion of the results follows in section 5. Section 6 summarises the implications for future research and concludes the paper.

2 Motivation and literature review

The goal of the present paper is to introduce a model of capability accumulation that (1) takes ideas from the microeconomic literature on how product innovation takes place and formulates them in a framework that is more similar to how macroeconomic models are built; (2) explores the the theoretical implications of recent empirical results on the relatedness or products and innovation processes. In this section, we first justify such an endeavour and then align the contribution with the existing literature.

[3] For a recent review see Aistleitner et al (2020).

2.1 Motivation: the case for models bridging the micro and macro ABM literature

Why is the development of models that bridge the micro and macro literature in the context of capability accumulation promising, and how does such an approach differ from what evolutionary macroeconomic agent-based models currently do? There is broad consensus when it comes to the empirical relevance of capabilities and their accumulation on various levels: while in the macroeconomic literature it is argued that "[...]countries tend to approach the level of income associated with the capability set available in them" (Hidalgo and Hausmann, 2009, p. 10570), others highlight the importance of capability accumulation on the firm level: "A firm's technological capabilities are central to its identity, its strategies, and its potential for success." (Aharonson and Schilling, 2016, p. 81). Statements such as these are underpinned by a vast amount of empirical findings both for the macro- as well as the firm-level (Aistleitner et al, 2020), and they are calling for models that integrate both micro- and macroeconomic dynamics.

This is exactly what macroeconomic agent-based models have been developed for (Hanappi and Scholz-Wäckerle, 2017; Dosi and Roventini, 2019). Such models, which aim for a comprehensive representation of the overall economy, however, face trade-offs when it comes to portraying complex mechanisms such as capability accumulation: by their nature they must consider all aspects of a macroeconomy, including households, firms, private and central banks as well as governments. Understandably, not all of them can be represented in maximum detail. Such an approach would go against the central idea of models, i.e. to focus on the essential aspects of the system under investigation. Moreover, it would also be practically infeasible.[4] Thus, even when agent-based models are meant to integrate mechanisms on the micro *and* macro level, they tend to take a bird's-eye view on what happens on the micro level, and focus on those aspects for which established routines and guideline models from the micro exist. Thus, there is room for models that try to bridge the gap between micro and macro models and to prepare the integration of certain mechanisms into macro models at a later stage. But not only do we hope that our model successfully synthesises work from evolutionary microeconomics that can later serve as a module within macroeconomic ABM, such intermediate models might also facilitate a feedback from macroeconomic models into microeconomics: Firstly, there are a number of mechanisms that affect capability accumulation that so far have been considered *only* in macroeconomic ABM literature, such as the role of industrial policy or public research.[5] Secondly, some insights such as the network of product relatedness (Hidalgo et al, 2007) originally come from the field of macroeconomics and, finally, mechanisms studied in microeconomics in isolation might function differently when they operate within a broader macro-like framework. To explore this possibility, models that include mechanisms from both the micro and the macro literature are required.

2.2 Previous research I: capability accumulation in macroeconomic ABM

Processes of capability accumulation are considered in the macroeconomic ABM literature mainly under the topic 'innovation' and/or 'technological change'. Although the various model families differ in details, a number of standard ways to model innovation have emerged. All of them stress the relevance of R&D investments, and most of them focus on process innovation, i.e. the accumulation of productive capabilities that make firms more productive, rather than enabling them to produce more or different products – with the exception of Ciarli et al (2018), which we will elaborate on below.

While most models feature both a consumption and a capital good sector, the locus of capability accumulation differs: In Dosi et al (2019b) and Caiani et al (2019) capability accumulation happens in the consumption good sector. Investment into R&D increases their chances to *innovate* – i.e. to increase their labour productivity – or to *imitate* – i.e. to copy the production technology of other firms, which might also result in increased labour productivity. Rengs et al (2019) extend upon the same logic by adding ecological concerns to the firms' decision problem: firms invest into R&D and then decide whether they try to increase their labour productivity or reduce CO_2 emissions associated with the production of their consumption goods. Here, the effect of the investment does not only depend on the firm itself, but also on spill-overs from firms in its environment.

[4] Arguably, the most comprehensive representation of an economy is the EURACE model of Dawid et al (2019). But even here, only selected aspects of the overall economy are represented in greater detail.

[5] For the effects of government activity, particularly public research, see Dosi et al (e.g. 2018), for industrial policy Dawid et al (e.g. 2018), and for the role of institutions see Caiani et al (e.g. 2019).

Central mechanism	Examples
R&D investment	Ciarli et al (2018), Dawid et al (2019), Hötte (2019), Dosi et al (2019b), Caiani et al (2019), Rengs et al (2019)
Spillovers among firms	Dosi et al (2019b), Caiani et al (2019), Rengs et al (2019)
Worker's experience	Dawid et al (2019), Hötte (2019)

Table 1: Capability accumulation in macroeconomic ABM.

Ciarli et al (2018) consider capability accumulation in both the consumption and capital sector: in the latter, investments into R&D enable capital good firms to produce capital goods that increase the productivity of consumption good firms – and that are therefore easier to sell at higher prices (this mechanism is also used in Hötte, 2019). In the consumption good sector, Ciarli et al (2018) features as one of the few macro ABM also some kind of product innovation: when consumption good firms invest into R&D they might come up with higher quality goods, which can then be sold to consumers at higher prices.[6]

A different kind of capability accumulation is discussed in Hötte (2019): in her model, *employees* learn to use certain capital goods and become more productive over time ('learning-by-doing'). They can then take this tacit knowledge with them to an other firm when they change their employer, thereby also adding a spillover dimension to the model. However, in the end this process also leads to increased productivity, thereby being in the effect similar to the models discussed above.

This cursory review of the literature[7] indicates that investment into R&D activities that improve productivity is by far the most common way to consider capability accumulation in macroeconomic ABM (see also table 1). Beyond that, various indirect channels of capability accumulation can be found in these models, e.g. the effect of innovation policy, public research or different labour market institutions. Nevertheless, all of them ultimately affect capability accumulation via their effect on the R&D investment of firms. Since R&D investment is indeed one of the major determinants of innovation and capability accumulation, this is not bad *per se*. Yet, it is important to keep in mind that such a treatment leaves aside the consideration of product innovation – which certainly is most relevant for the developmental implications of innovation processes (Hausmann et al, 2007; Hidalgo et al, 2007) . In alternative modelling frameworks, such as endogenous growth theory, the so-called *expanding variety models* that stand in the tradition of Grossman and Helpman (1991b,a) *do* feature some kind of product innovation, but even here, the focus is on product varieties rather than new products. Models that explain how firms learn to produce different products such as those falling into different SITC or HC categories, are still to be developed on the macroeconomic level. The model discussed in section 3 is intended to be a first step in such a direction.

2.3 Previous research II: capability accumulation in microeconomic ABM

A number of evolutionary models have been used to study processes of capability accumulation on the micro (and meso) level.

The approach of modelling distinct products as nodes on a technology space followed in section 3 is similar to Caiani (2017), where firms can use both imitative and innovative strategies to improve their chances of getting more productive by investing into R&D activities. He also uses a technology space to model technological change, yet the nodes of his network represent technologies that allow firms to produce a homogeneous product more productively, not the abilities to produce different products. This is different in Wersching (2010), who uses a circular technology space where nodes actually represent different product varieties. In contrast to the model proposed in this paper, he does not focus on *how* the structure of the knowledge space impacts innovation dynamics. Rather, he focuses on the distinction between *incremental* and *radical* innovation and their dynamics, as well as the impact of differing degrees of

[6] This is not product innovation in the narrow sense, but more in the spirit of the expanding variety models of Grossman and Helpman (1991b), where the focus is not on the invention of entirely new products, but varieties of existing ones.

[7] For a more detailed review see, e.g., Aistleitner et al (2020), or, for a review of macroeconomic ABM in general Dawid and Delli Gatti (2018) or Dosi and Roventini (2019).

competition among innovators and the effect of different technological regimes such as 'Schumpeter Mark I' and 'Mark II'. In Savin and Egbetokun (2016), firms are situated on a two-dimensional 'knowledge space' and need to distribute their R&D expenses between the creation of new knowledge and their absorptive capacities, the latter measuring their ability to absorb existing knowledge. Knowledge can spill over voluntarily if firms engage in research alliances, or involuntarily via absorptive capacities. The authors then go on to study the emerging alliance networks under various parameter constellations. Although it is different with regard to the overall purpose, their model is therefore related to that proposed in 3. A more conceptual approach is taken by Silverberg and Verspagen (2005). In their model, new technologies build upon existing technologies on a percolation space. By doing this, the model captures the fundamental idea of relatedness between old and new technologies (or products) and is capable of reproducing several stylised facts, such as the size distribution of innovation. If compared with the models discussed before, this concept is more abstract and it is not suited to study the implications of different topological structures of product relatedness. However, it does allow for an open-ended technological evolution.

A slightly different perspective is described in Desmarchelier et al (2018), where firms are decide what products to produce and to export. Depending on their capabilities, they can move to products that are related to those that they currently produce. Values for relatedness are taken directly from empirical data, and firms take into account the number of competitors in their neighbouring products, as well as their complexity and expected prices. This way, the model is able to replicate the the empirical observations of Hidalgo and Hausmann (2009) on the product space, i.e. the empirical network of products and their relatedness, for numerous Asian countries. Such an approach is related to the one pursued here, yet it differs from the model below in that the mechanisms that are taken into account are modelled on a more aggregated level and it does not explore the implications of different product space topologies or complexity distributions.

An alternative to using a technology space is to model information pieces directly, and to let firms recombine these information pieces into newer and more complex technologies. While this approach is missing two important advantages of the technology space, i.e. the simplicity when it comes to studying the implications of different topological structures of relatedness and the potential to be calibrated against data, it allows for an open-ended technological progress.

One example for such an approach is Arthur and Polak (2006), who discuss a model in which the elements of technologies are logic circuits. Newer technological circuits are built from existing ones, and their performance is measured by letting the logical circuits perform some pre-defined logical tasks. The authors find that logical circuits become more and more complex and sophisticated over time. A similar idea is pursued in Vermeulen and Pyka (2014), where the authors also show how collaboration and information sharing among firms allows them to come up with more complex inventions. A more abstract approach is taken in the 'Bit Economy' as introduced by Angus and Newnham (2013), which is a highly idealised economy that is populated by a finite number of state automata that are processing existing and developing new bit-strings. This process can be interpreted as developing new technologies or products, and functions without any structural assumptions on production or consumption. Nevertheless, the model does replicate some stylised facts of innovation processes, such as the relatedness of patents and growth of innovations. In all, it is more abstract than the one introduced in section 3. It is less concerned with the economic mechanisms underlying innovation processes and can be understood as a general thought experiment on how more complex technologies emerge over time.

A more applied model that explicitly represents the process of re-combining existing technologies into new ones is presented in Pyka et al (2019), who focus on three major determinants of capability accumulation on the firm and regional level: *R&D investment*, *alliances* and *learning-by-doing*. New products are assembled by recombining existing knowledge units and can then be sold to consumers. Firms accumulate productive capabilities by acquiring new knowledge units. This might happen (a) via direct investment into R&D, which creates new knowledge units that are necessarily similar to existing ones, (b) by copying those parts of knowledge units from partner firms that are not tacit and (c) simply via *learning by doing*. The main focus of this is not on the exploration of new technologies by the firms but rather on the investigation of channels of firm interaction and cooperation, as well as of the effectiveness of policies

Central mechanisms	Examples using a technology space	Examples using an explicit representation of knowledge units
Alliances and cooperation	Savin and Egbetokun (2016)	Tur and Azagra-Caro (2018), Pyka et al (2019)
Absorptive capacities & spillovers	Wersching (2010), Caiani (2017)	Pyka et al (2019)
Recombination of existing knowledge	Silverberg and Verspagen (2005)	Arthur and Polak (2006), Angus and Newnham (2013), Vermeulen and Pyka (2014)

Table 2: Capability accumulation in microeconomic ABM.

fostering cooperation.

In all, as indicated in table 2, microeconomic models tend to concentrate on a different set of mechanisms than the macroeconomic models discussed in the previous section. Here, the focus is less on mechanisms involving the state and institutions, but more on mechanisms operating within or between single firms. As the short review of the empirical literature in the next section shows, both of the literature branches highlight important aspects of capability accumulation.

2.4 Previous research III: the empirics of capability accumulation and product innovation

The empirical literature on capability accumulation is large and distributed among various disciplines (for a recent review see Aistleitner et al, 2020). Table 3 lists some exemplary references for the empirical results that are relevant for the design of the model introduced below.

One of the most frequently highlighted factors that determine the accumulation of capabilities are *absorptive capacities* of firms, which have originally been defined as a firm's ability to "to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal, 1990, p. 128). While nowadays the definition of absorptive capacities varies throughout studies, there are two effects that authors largely agree upon: First, absorptive capacities make it easier for a firm to evaluate its environment and make it more adaptable to changes. Second, absorptive capacities make it easier to acquire *involuntary* spillovers, i.e. spillovers that occur without the cooperation of other firms.

Another empirical regularity that enjoys wide support is the idea of *relatedness*, i.e. the fact that new capabilities are somehow related to capabilities that already exist. For example, Neffke and Henning (2013) find that firms are more likely to diversify into industries that require skills that are related to those that they are already working with, and Aeron and Jain (2015) gather evidence on how firms actually develop new insights by experimenting with recombinations of existing knowledge ('bricolage').

Not surprisingly, the empirical literature has also documented the relevance of R&D spending (e.g. Chung and Lee, 2015), research cooperation (e.g. Subramanian et al, 2018) and learning-by-doing (e.g. Dosi et al, 2019a). More nuanced are results on the role of labour market institutions, where some find positive effects of more flexible labour market regulation (e.g.) while others find such flexibility to be detrimental (e.g. Kleinknecht et al, 2016). Similarly, the majority of studies on governance structures are case studies that highlight very nuanced and diverse effects of different firm government structures (e.g. Figueiredo, 2008; Collinson and Wang, 2012). Thus, while it is clear that this is an important area for further research, up till now, there are no general results that present themselves immediately for models.

The model discussed below is not intended to be a comprehensive framework that accounts for all the stylised facts just referenced in table 3. Rather, we focus on some of them that are (1) uncontroversial and (2) that have not yet gained a lot of attention in the literature. More precisely, we aspire to build a model that features different products, and with which we can explore the implications of various topological structures of relatedness among them for innovation

Relevant factor/result	Selected references
Absorptive capacitites	Chuang and Hobday (2013); Chung and Lee (2015); Figueiredo and Cohen (2019)
Alliances & spillovers	Cantwell and Zhang (2013); Wu and Wei (2013); Subramanian et al (2018)
Experience and *learning-by-doing*	Villar et al (2012); Dosi et al (2019a)
Firm governance structure	Figueiredo (2008); Collinson and Wang (2012)
Labor market institutions	Kleinknecht et al (2016); Cetrulo et al (2018)
R&D spending	Figueiredo (2008); Wu and Wei (2013); Chung and Lee (2015)
Relatedness of innovations	Neffke and Henning (2013); Aeron and Jain (2015); Hidalgo et al (2018)

Table 3: Empirical results on the determinants of firm capabilities.

dynamics. This is an endeavour worth undertaking since the relatedness of products has been highlighted as an essential fact in the empirical literature, but has not been adequately considered in existing macroeconomic models. At the same time, while a number of microeconomic models do consider relatedness of innovations, there is no model that studies the implications of different topological structures, or the distribution of product complexity within the network. What is more, in our model the respective roles of absorptive capacities and R&D investment are considered – two factors that have also been highlighted in the empirical literature. To keep the complexity of the model manageable, we do not consider research cooperation among firms, learning by doing or spillovers, since these channels have been at the centre of respectable models for quite a while. Moreover, we leave the study of different firm government structures for further research since the empirical literature has not yet come up with concrete and decisive results that could inform general models. These decisions also pay tribute to the goal of developing a model that is simple enough to prepare a model that can be used within macroeconomic models in the future.

3 Model Description

The model seeks to integrate a heterogeneous product space into an agent-based model of innovation. In the future, it might be used as a bridging vehicle between micro and macroeconomic models. In this first step, however, the focus is exclusively on the production side of the economy, leaving the demand sector largely unexplored and not operating within a stock-flow consistent framework. A main priority is the investigation of the effects of different structural properties of the product space.

The model, therefore, consists of M firms that produce N heterogeneous products.[8] Firms move around the product space and can produce only the product that matches their current location. They invest into various kinds of R&D activities and sell their products in exogenously constrained markets. The main question is how different topological structures of the product space, and different distributional assumptions on product complexity affect the innovation and production dynamics of the model.

3.1 The Product Space

The model features heterogeneous products that differ in their complexity and and their mutual relatedness. To represent products we use an artificial product space that follows the empirical work of Hidalgo and Hausmann (2009) and plays the role of the 'technology space' in the models discussed in section 2.3. A product space is a weighted network $\mathcal{G}(V, E)$ with $V(\mathcal{G}) = \{v_1, ..., v_n\}$ vertices and $E(\mathcal{G}) = \{e_1, ..., e_n\} \subseteq V \times V$ edges. Any edge $e_i \in E$ connects two vertices such that $e_i^{jk} = \langle v_j, v_k \rangle$ with $v_j, v_k \in V$. Each vertex v_i represents one product. Firms can move around the

[8] An overview over the parameters of the model and the chosen baseline values is given in table 5.

Topology of the product space		
Network	**Parameters**	**Baseline values**
Complete	-	-
Power-law cluster	Edges wired from new nodes m and probability to close triples to triangles p	$m = 4, p = 0.7$
Random ('Erdös-Rényi')	Probability that an edge exists p	$p = 0.25$
Regular network	Degree of every node m	$m = 4$
Ring	Number of wired neighbors m	$m = 2$
Scale-free ('Barabási-Albert')	Edges wired from new nodes m	$m = 4$
Allocation of complexity values		
Kind	**Description**	
Random allocation	Complexity values are distributed randomly among all products.	
Weighted degree	Complexity correlates strongly with vertex weight.	
Eigenvector centrality	Complexity correlates strongly with eigenvector centrality.	
Closeness centrality	Complexity correlates strongly with closeness centrality.	

Table 4: The structural properties of the product space to be studied in the model. A complete list of model parameters is given below in table 5.

product space and can only produce the product on which they are currently located.[9] Each product is characterised by its *complexity*, v_i^c , which is a measure for the sophisticatedness of the product. Following the 'principle of relatedness' (Hidalgo et al, 2018), firms that produce a certain product cannot arbitrarily diversify into the production of any other product but can only diversify along the edges of the network. In the model, firms can move at most one edge at a time and passing edges towards a more related product is easier than moving to more 'distant' ones. The distance between two vertices $\phi(v_j, v_k) = \omega(\langle v_j, v_k \rangle) = \omega(e_i^{jk})$ is the inverse of the relatedness of the two neighbouring products, i.e. their similarity in terms of the capabilities needed to produce them. In the present model, this is the normalized difference of their complexity values, i.e. $\omega(e_i^{jk}) = \frac{|v_i^c - v_j^c|}{\max\{|v_i^c - v_j^c|\}_{i,j \in V}}$.

Empirical product spaces are derived from export data and deviate strongly from simple and complete networks, but feature complex core-periphery-like structures (e.g. Hidalgo et al, 2007). Therefore, we study the impact of different topological structures and distributions of product complexity on innovation dynamics. Tp this end, distinct artificial product spaces with pre-specified properties are created and the resulting model dynamics for such specification are investigated. More precisely, of interest are (1) the impact of different network topologies, (2) the relationship between product complexity and centrality as well as (3) the relevance of complexity for prices (see also table 4).[10]

With regard to different topologies we distinguish between a *complete* network, in which each vertex is connected to every other vertex; a *regular* network, in which each vertex is connected to m other vertices; a *ring* where every vertex is connected to two neighbours; a *Barabási-Albert* network (Barabási and Albert, 1999), which is characterised by its scale free degree degree distribution; a *power law cluster network* that is characterised by both a power law degree distribution and large clustering (Holme and Kim, 2002) as well as a random ('Erdös-Rényi') network (Erdös and Rényi, 1959) in which each edge exists with the same probability p (see figure 1 for an illustration). The model is also used to study whether the relationship between product complexity and centrality in the product space has an impact on the model dynamics. To this end, complexity values are either distributed randomly, or according to the

[9]In the beginning of the simulation, firms are allocated in the locations that have the smallest Eigenvector centrality. This way we ensure that firms start in the periphery of the product space, if such a periphery exists.

[10]The results carry a broader theoretical relevance: many studies implicitly assume a complete product space with uniform distribution of complexity since all products are in principle the same and can be invented irrespective of the currently produced products. The results here help illustrating the relevance of this often implicit assumption.

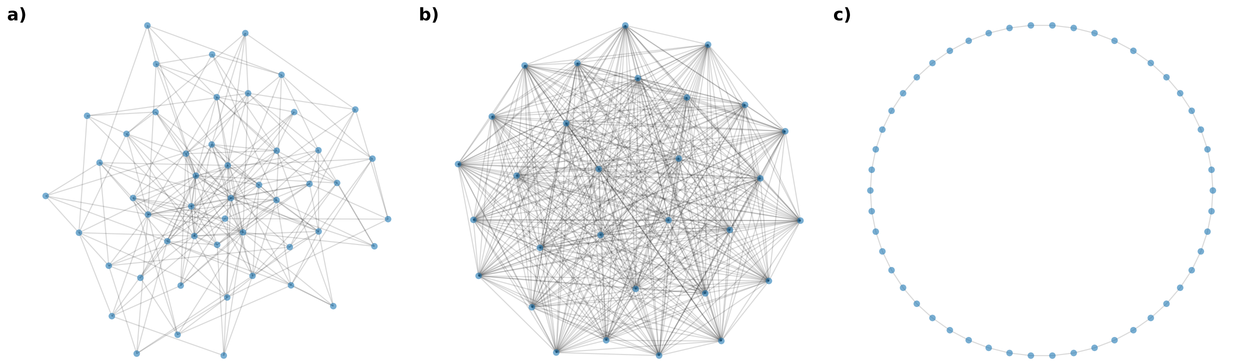

Figure 1: Different kinds of topologies for the product space. Panel (a) shows a scale-free ('Barabási-Albert'), panel (b) a complete and (c) a ring network with 30 products each.

weighted Degree, Eigenvector or Closeness centrality or the products. Finally, as will be described in more detail below, the model is used to study how the relevance of complexity for product prices impacts on the overall dynamics.

3.2 Timeline of Events

The model is analysed using Monte Carlo simulations. For each parameter constellation, we run the model 50 times and compute summary statistics. Each single run begins with the allocation of the N firms, which are initially endowed with the same initial stock of capital and capabilities, on randomly selected positions on the product space. To ensure that firms start on different locations in the periphery of the product space, they are placed on the products with the lowest Eigenvector centrality. Then each of the t time steps goes through the following routines:

1. Computation of prices according to the firm positions on the product space
2. Output gets produced and firm profit realized
3. Firms decide on their new position on the product space
4. Firms make their investment decisions
5. R&D takes place and firms make their actual move on the product space

The single steps are now described in more detail.

3.3 Price determination

Under usual circumstances, prices would form endogenously by firms offering products at certain prices, which depend on their expenses for wages and their experience with sold products in the past.[11] However, since the present model is meant to focus on the production side of the economy and does not feature proper households, prices are set in a more simplistic manner. Assuming q_{ij}^t denotes the output of firm j for good i in t the price of good i is given by:

$$p_{it} = \frac{v_i^c \cdot \alpha}{\sum_{j=1}^{N} q_{ij}^t} \tag{1}$$

The parameter α is fixed and determines the impact of product complexity v_i^c on the price of product i. Varying α across simulations allows an exploration of how varying relevance of product complexity for prices impacts the model dynamics (see section 4 below). Moreover, we assume that there is a saturation threshold for each product, i.e. only a finite amount of q_i^{max} can be sold for every product. For now $q_i^{max} = q^{max} \forall i \in N$, i.e. the threshold is the same for all products. Although the overall formula is too simplistic to count as a realistic representation of true price formation processes, it is sufficient for the purposes at hand since it captures both the fact that a larger supply of the product comes, *ceteris paribus*, with lower prices and higher product complexity is, *ceteris paribus*, associated with higher prices.

[11] The common price setting strategies in macroeconomic ABM are summarised, e.g., in Dawid and Delli Gatti (2018).

3.4 Production of goods

Firms produce the product that belongs to their current position on the product space using the capital stock they have accumulated so far. The desired output of firm j of good i in t is given by

$$\hat{q}^t_{ij} = \min\left[A_{jt}k_{jt-1}, q^{max}\right] \tag{2}$$

where k_{jt-1} is the capital stock of firm j from the previous period and A_{jt} is capital productivity. In the current version $A_{jt} = A\forall t, j$, that is, our focus here is on *product* rather than *process* innovation. Moreover, no firm aims to produce more than the theoretical maximum amount that could be sold if the firm was a monopolist for i, i.e. q^{max}.

Then, for all products for which $\sum_{j=1}^{M} \hat{q}^t_{ij} > q^{max}$, i.e. where the total aspired output of firms exceeds the maximum demand q^{max}, the actual sold output for firm j, q^t_{ij}, is determined according to its theoretical market share $s^t_{ji} = \frac{\hat{q}^t_{ij}}{\sum_{j=1}^{M}\hat{q}_{ij}}$:

$$q^t_{ij} = s_{ji}q^{max} \tag{3}$$

The difference $\hat{q}^t_{ij} - q^t_{ij}$ is added to the firm's inventories, R_{ji}, which it then tries to sell at a later period.

3.5 Computation of profits

The profits of firm i are given by the product of q^t_{ij} and p_{it}, subtracting capital costs ($\mathcal{C} \cdot k_{jt-1}$) and, if relevant, paybacks for previous loans from banks (l_{jt}), as well as receiving interest for deposits or paying interests on loans (r_{jt}):

$$\mathbb{E}(\Pi_{ij}) = q^t_{ij} \cdot p_{it-1} - \mathcal{C} \cdot k_{jt-1} + r_{jt} - l_{jt} \tag{4}$$

Before the firm decides into what the profit is to be invested, it considers moving to a different location on the product space for the next round.

3.6 Location choices of firms

In each time step, firms search for information on more profitable production opportunities and – if they find one – they invest into different capability measures in order to reach the more profitable product on the product space.[12] Thus, before each firm decides on what capability measures to invest in (which will be discussed in the next subsection), firms choose a target that their capability measures will be aimed at.

First, firm j considers all products that are within its *range of vision* Υ_{jt}. The latter is initially set to unity for all firms, indicating that each firm can see (i.e. has information on) only the closest product on the product space. During the model runs, firms try to extend their range of vision in order to gain more knowledge on the product space and to be able to better assess the value of their environment. This is a part of their *absorptive capacity* and is described below.

The set of all visible products $\mathcal{V} = \{v_1, v_2, ..., v_\upsilon\}$ consists of the υ closest products to the current position of the firm. Note that these are not necessarily the immediate neighbour products: if the weighted distance to a product that is two vertices away is smaller than the weighted distance to an immediate neighbour, the latter might not be in $\mathcal{V}$.

For all products in $\mathcal{V}$, the firm then computes the expected profit for a scenario in which it was successfully moved to that product. As a heuristic, the firm takes the current amount of the product that gets produced, adds its own production capacity and divides this by the number of firms in the market plus one, correcting for potential overproduction. Formally, if Q_{it-1} is the total output of good i in the previous round, q_{jt-1} the production capacity of the firm from the previous round and n_{it-1} the number of firms producing good i in the previous round, then firm j computes expected profits for good i as:

$$\Pi^t_{ij} = \begin{cases} \frac{Q_{it-1}+q_{jt-1}}{n_{it-1}+1} \cdot p_{it-1} - \mathcal{C} \cdot k_{jt-1} + r_{jt} - l_{jt}, & \text{if } Q_{it-1} + q_{jt-1} \leq q^{max} \\ \frac{q^{max}}{n_{it-1}+1} \cdot p_{it-1} - \mathcal{C} \cdot k_{jt-1} + r_{jt} - l_{jt}, & \text{otherwise} \end{cases} \tag{5}$$

[12]In this model, following the literature outlined in section 2.4, the capability measures that a firm can choose to implement are investment into *absorptive capacities* and into *R&D*. They will be explained below.

where $\mathcal{C}$ is the cost share (which is given as a parameter), k_{jt-1} the current capital stock (which has been determined in the previous round), r_{jt} the interest payments to or from the bank, depending on whether the firm has loans or deposits, and l_{jt} potential paybacks for loans to the bank - how the two latter values are computed is explained below.

The ultimate target product is then the product for which $\mathbb{E}(\Pi_i^*)$ is highest.[13] As already mentioned above, the price of each product increases with its complexity and decreases with market size. Therefore, the chosen target product will not necessarily be the most complex product in the range of vision.

3.7 Actual investment decisions of the firm

Once profits are received and the current target product is determined, the firm computes its actual investments. To this end, it first computes *desired* investments, then it will start negotiating with the bank for a possible loan, the amount of which determines *actual* investment.

Desired Investment

The highest priority of firms is to maximise profits in their current market. To this end, firms invest into the accumulation of their capital stock, thereby controlling their future output capacities. Firms aspire to be able to sell some desired output: $\hat{q}_{ij}^{t+1} = q_{ij}^t + q^{max} - \sum_{j=1}^N q_{ij}^t - R_{ij}^t$, which is oriented on current output, but takes into account the option for expansion that is given by $q^{max} - \sum_{j=1}^N q_{ij}^t$, as well as current inventory R_{ij}^t. Desired investment in capital stock $I_{k,jt}$ is then computed as:

$$\hat{I}_{k,jt} = \begin{cases} \frac{\hat{q}_{ij}^{t+1}}{A_{jt}} + \delta \cdot k_{jt-1}, & \text{if } \hat{q}_{ij}^{t+1} \geq 0 \\ \delta \cdot k_{jt-1}, & \text{otherwise} \end{cases} \tag{6}$$

where δ denotes the depreciation rate of capital. That is, in the case that the firm does not wish to extend its production, it intends to invest sufficiently in order to compensate for the depreciation of capital.

Since having information on the product space is crucial for choosing successful paths, the next priority of firms is to broaden their *range of vision* Υ_j. Therefore, the firms' demand for investment into information is chosen such that the probability of success is equal to some parameter τ that denotes their probability target.[14] Following Caiani (2017, p. 320), there is an upper limit to capability-measure investment that is set to 12% of firms' capital stock and the probability of success $\mathbb{P}_\Upsilon$ is computed as

$$\mathbb{P}_{\Upsilon,jt} = p_\Upsilon \cdot I_{AC,jt} \cdot k_{jt-1}, \tag{7}$$

where the size of the parameter p_Υ is decisive for the probability of success. That is, the higher the share of investment into absorptive capacities $I_{AC,jt}$ and the higher the capital stock, the higher the probability that the extension of information is successful. Desired investment $\hat{I}_{\Upsilon,jt}$ into information is then given as

$$\hat{I}_{\Upsilon,jt} = \frac{\tau}{p_\Upsilon \cdot k_{jt-1}}. \tag{8}$$

It is worth mentioning that a firm always aims to extend its range of vision, regardless of its situation in the market and the product space.

If a firm was not able to find a more profitable product than the one it is already producing, it has no further desire to expand its capabilities.[15] The same goes if the firm's capabilities to produce the target product are already sufficient (conditions for this will be explained below). Otherwise, the preferred capability accumulation measure depends on whether there already is a market for the chosen product or not. In the case that the product is already produced by

[13]Since firms can only move on vertex a time the desired target vertex might not be in its current reach. In this case the firm will first move to a neighbour that brings it closer to the target vertex and continues its journey in the next time step.

[14]For an overview of all parameters, see table 5.

[15]This assumption is reasonable since in the present case only product innovation is considered. In other circumstances, firms would of course have continued interest in expanding their capabilities, particularly with regard to their productivity ('process innovation').

other firms, the firm opts for absorptive capacities, hoping to be able to learn from and imitate the firms that are already producing the target product. As before, demand for investment into spillover capabilities is chosen such that the probability of success is equal to some parameter τ that denotes their probability target, where the probability of success of spillover investment $\mathbb{P}_{\Phi,jt}$ is computed as

$$\mathbb{P}_{\Phi,jt} = p_{\Phi} \cdot I_{AC,jt} \cdot k_{jt-1}, \tag{9}$$

leading to a demand for investment into spillover capabilities of

$$\hat{I}_{\Phi,jt} = \frac{\tau}{p_{\Phi} \cdot k_{jt-1}}. \tag{10}$$

Total desired investment in absorptive capacities $\hat{I}_{AC,jt}$ is then computed as the maximum of demand for information and spillover investment:

$$\hat{I}_{AC,jt} = \max(\hat{I}_{\Upsilon,jt}, \hat{I}_{\Phi,jt}). \tag{11}$$

By investing into R&D, firms can learn how to produce a product without being dependent on spillovers from other firms. This measure is especially important in order to learn to produce new products that are not yet produced by other firms. In the case that the current target product is not yet produced by other firms, the firm will therefore choose to invest into R&D in order to learn everything that is necessary to innovate and change production. Again, demand for investment into R&D is computed analogously such that the probability of success is equal to the target probability τ. Success is given as

$$\mathbb{P}_{X,jt} = p_X \cdot I_{X,jt} \cdot k_{jt-1}, \tag{12}$$

and, accordingly, demand for investment in R&D is:

$$\hat{I}_{X,jt} = \frac{\tau}{p_X k_{jt-1}}. \tag{13}$$

The total demand for investment, then, simply is computed as the sum of demand for investment into capital stock and capability measures:

$$\hat{I}_{jt} = \hat{I}_{K,jt} + \hat{I}_{AC,jt} + \hat{I}_{X,jt} \tag{14}$$

Bank negotiations

In case that total profits are not sufficient to cover desired investment, the respective firm applies for a loan with the single representative bank. The amount of a loan that the bank is possibly willing to grant is dependent on the firm's rate of return and a financial-regime parameter β:

$$L_j^t = \beta \frac{\Pi_{ij}^t}{k_{jt-1}} \tag{15}$$

Thus, the complete financial constraint for the firm is given by $\theta = \Pi_{ij}^t + L_j^t$. This constraint then determines the actual investments.

Actual Investment

As indicated above, the main priority of firms lies in optimizing their current production, and, therefore, to satisfy their demand for investment in capital stock:

$$I_{k,ij}^t = \begin{cases} \hat{I}_{K,ij}^t, & \text{if } \hat{I}_{K,ij}^t \leq \theta \\ \theta, & \text{otherwise} \end{cases} \tag{16}$$

If, after this investment, the financial constraint is not fully exhausted, firms invest into capability measures, where absorptive capacities measures are given higher priority than R&D measures due to the priority of extending range of vision:

$$I^t_{AC,ij} = \begin{cases} \hat{I}^t_{AC,ij}, & \text{if } \hat{I}^t_{AC,ij} \leq \theta - I^t_{k,ij} \\ \theta - I^t_{k,ij}, & \text{otherwise} \end{cases} \tag{17}$$

$$I^t_{X,ij} = \begin{cases} \hat{I}^t_{X,ij}, & \text{if } \hat{I}^t_{X,ij} \leq \theta - I^t_{k,ij} - I^t_{AC,ij} \\ \theta - I^t_{k,ij} - I^t_{AC,ij}, & \text{otherwise} \end{cases} \tag{18}$$

If the entire demand for investment was fulfilled and the financial constraint is still not fully exhausted, the rest goes into the firm's bank account m_j.

3.8 Conduct capability measures and make the move on the product space

After computing their actual investment, capability measures take place. Their success is determined by a Bernoulli process for which probabilities are given by equations 7, 9 and 12. If R&D was successful, the firm's R&D capabilities X_j are increased. The firm can now move to the current target product if $X_j \geq v^c_i$, i.e. if its R&D capabilities are greater than or equal to the complexity value of the target product. Else, if spillover investment was successful, spillover capabilities Φ are increased. The target product can now be reached if $\Phi_j \cdot n_i \geq v^c_i$, that is, if spillover capabilities multiplied by the number of firms in the market for the new product n_i are greater than or equal to the complexity of the target product. Evidently, entering the market for a new product becomes easier the more firms are already producing it. Finally, if investment in information is successful, the firm's range of vision Υ_j is increased by 1, improving the information the firm has on hand to choose its target product in the next period.

At the end of each period, the firm's capital stock k_j and bank account m_j are updated:

$$k_{jt} = (1 - \delta)k_{jt-1} + I^t_{k,ij} \tag{19}$$

and

$$m_{jt} = m_{jt-1} - l_{jt} - L_{jt} + (\theta - I_{jt}), \tag{20}$$

where $(\theta - I_{jt})$ is the amount of profit and loans that were not spent on investment.

4 Model Results

The model is analysed using Monte Carlo simulations for which the model is run 50 times with 250 time steps each. Figure 2 – which visualises the dynamics of the share of produced products, their prices and average complexity for different product space topologies – indicates that this is a reasonable time horizon to study, since the state variables of interest seem to have approached a relatively stable basin of attraction.[16] The baseline parametrisation is summarised in table 5.

In the following the focus of the discussion will be on the impact of (1) different topological structures of the product space (section 4.1), (2) the relationship between the product position within the product space and its complexity (section 4.2) as well as (3) the relevance of product complexity for the price (parameter α above, section 4.3) on (a) the share of actually produced products, (b) prices of produced products and (c) their average complexity. In case the reader wishes to replicate the results or conduct alternative simulation exercises they can find the code of the model on Github.[17]

4.1 The impact of different product space topologies

Figure 2 represents the model dynamics for different topological structures of the product space. Noticeably, although the dynamics are not trivial the state variables settle to a rather stable basin of attraction towards the end, event if not all variables approach a fixed point equilibrium. Therefore – and to get a better view on the inter-run variation – figure 3 visualises the situation at the end of the simulation, i.e. at $t = 250$, using using the median and the interquartile-range

[16] This does not mean that all variables approach a fixed point attractor. Prices, for example, seem to have approached a limit circle.

[17] The URL of the repository is BLINDED FOR REVIEW.

Parameter	Baseline value
Number of firms	100
Number of banks	1
Number of time steps	250
Number of products	100
Relevance of complexity α	100
Demand saturation q^{max}	75
Initial capital k_0	50
Financial regime	2.5
Depreciation rate	3%
Productivity A	0.5
Cost share $\mathcal{C}$	0.25
Interests on deposits	1%
Interests on loans	4%
Payback rate	5%
Probability target τ	0.5
Information success parameter p_Υ	0.12
Spillover success parameter p_Φ	0.09
R&D success parameter p_X	0.06
Initial range of vision Υ	1
Initial spillover capabilities Φ	0.1
Initial R&D capabilities X	0.1

Table 5: The baseline parametrization of the model. If not mentioned differently, the results in this section were derived using these parameter settings.

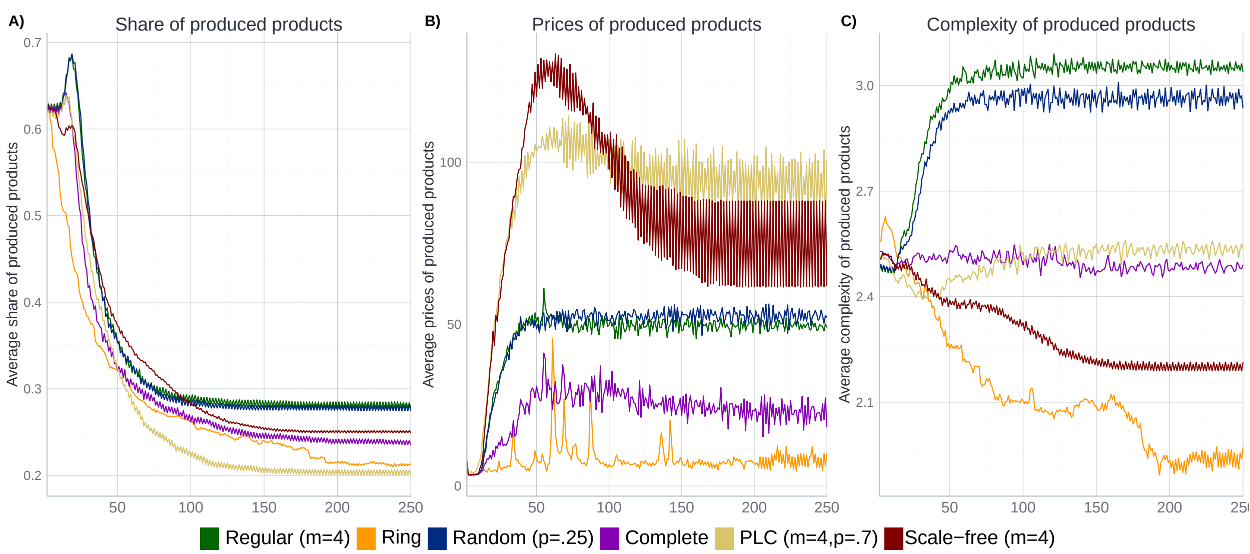

Figure 2: The dynamics of the model for different product space topologies. The remaining parameters are set as in table 5. The lines show average results for 50 simulation runs.

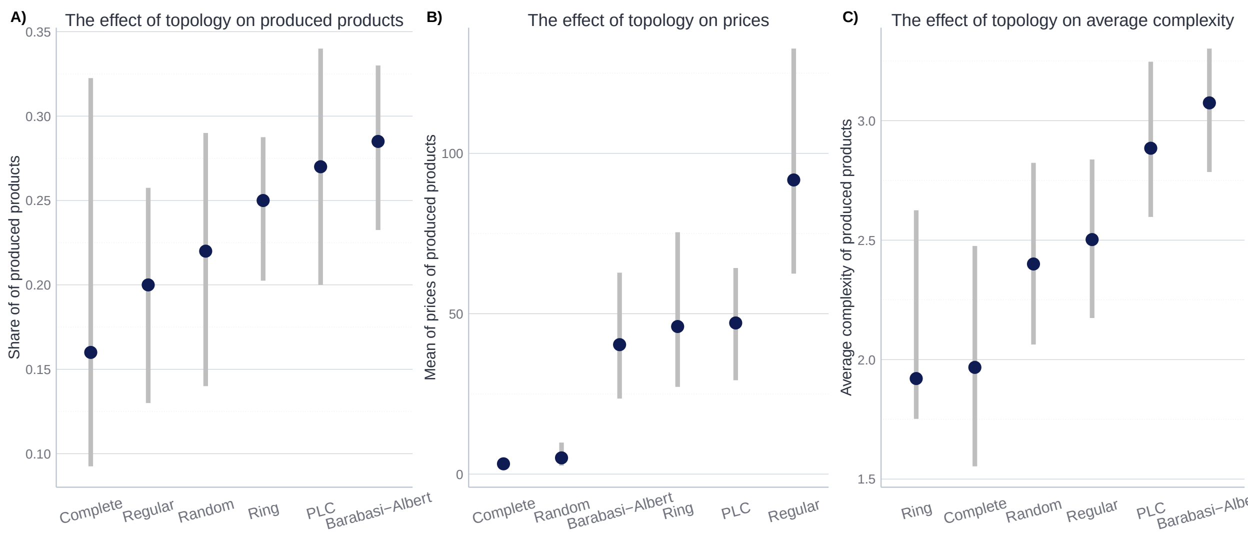

Figure 3: The effect of different product space topologies. The figure shows median results after 250 steps of 50 iterations of the model, i.e. the situation during the final time step in figure 2. The other parameters are set to their baseline level described in table 5. The dots represent the median result, the lines the interquartile-range (IQR).

(IQR) of the simulations. A visualisation of the dynamics can be found in the online appendix, yet they do not add much to the arguments made below.

The first immediate observation that can be inferred from both figures is that the topological structure of the product space does matter: there is apparent variation across parameter constellations. With regard to share of actually produced products (figure 3A) we see that the variety of the products increases with the modularity of the product space. Topologies that feature locally well-connected but globally rather isolated structures, such as the Barabási-Albert or the power-law-cluster graph, are associated with a larger share of produced products: here, firms tend to get stuck in these closely connected areas, which are more difficult to be left in favour of a different community of products, which prevents an overall convergence on more complex products. The ring network here takes an intermediate position in the results since while it does not feature proper clustering, it does make it difficult for firms to move to entirely different locations due to the sparse neighbourhood structure. The random and regular networks do not feature much of a community structure, which is why firms move along the product space more easily and may converge more rapidly on a particular set of products. The complete network, while featuring the lowest median (and average) values for the share of produced products, shows considerable more intra-run variation than the other constellations. Thus, it seems to be more difficult to predict what will happen if the product space is fully connected. From a theoretical viewpoint this result is particularly interesting since many models implicitly assume a complete product space when they assume that any kind of innovation is possible at any time. The results, however, indicate that studying deviations from this implicit special case are worth exploring: not only do deviations matter, other topologies also are associated with less inter-run variation.

Once we consider the prices and complexity of the produced products we also see the complete network to take a quite distinctive place in the results. Since all products are connected with each other it is more difficult for the firms to find more complex products (since they always start in the periphery of the product space), so they can also charge only small prices, despite being more distributed across the space. For networks where the most complex products are in the centre of separated communities, such as the Barabási-Albert or the PLC network, it is easier for firms to find these products, but since this also comes with a stronger concentration of firms producing them, prices increase only moderately as compared to the complete network. Although the final effect is similar, the opposite happens on ring networks: here, the average complexity is low since firms find it difficult to move effectively towards more complex products due to the small neighbourhood structures, but because of the resulting dispersion, prices are moderate. The

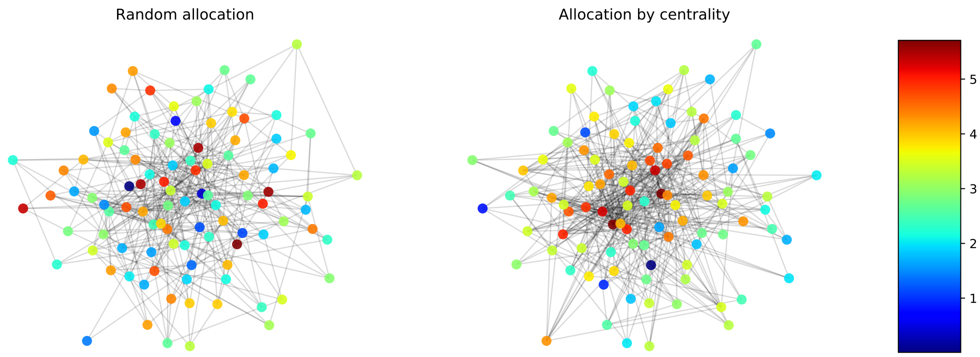

Figure 4: The left plot shows a product space with randomly allocated complexity values. On the right, more central products tend to have higher complexity.

highest prices can be observed on the regular network, which is also intuitive since there are no clusters in which firms can get stuck and medium to high complexity products are easier to reach from everywhere. While this makes is relatively harder to identify these products than in a clustered network, it facilitates the evasion of competition, leading, in the end, to higher prices than in clustered networks where average product complexity is higher.

In all, we find that the topology of the product space, which can be thought of as a representation of the relatedness-structure of the products in the economy, does have an impact on the innovation dynamics in the model. Complete networks, which are often implicitly assumed in models that model innovation as purely stochastic processes, imply rather distinct effects, so an exploration of alternative topologies is worthwhile, but also not trivial: the interpretation of their effects is not easy and requires a close look on the actual mechanisms underlying the innovation process.

4.2 Relevance of the allocation of complexity

In real-world product spaces, more central products tend to be more complex (Hidalgo et al, 2007; Hidalgo and Hausmann, 2009). Is this feature theoretically relevant for the dynamics of product innovation? In other words, does it matter whether product complexity is distributed randomly across the product space, as in the left network in figure 4, or whether complexity correlates with centrality such that the most central products are assigned the highest complexity values, as is the case in the right network in figure 4?

A nuanced answer is provided in figure 5: first, while it does not matter very much according to *which* centrality measure complexity values are allocated, there is a considerable difference between cases where complexity correlates with centrality and where it does not. Second, the effect is least pronounced when it comes to the share of produced products, although there are more products produced in the random case. This is because in this situation complex products are more dispersed across the product space and for firms it is easier to avoid competition by moving to other products with moderate complexity. Yet, this effect is minor and the huge inter-run variability for the random case must be kept in mind. Third, the effect is most pronounced when it comes to the average complexity of the produced products. This is less surprising since central products are easier to find on the product space and in the case of non-random complexity allocation the complexity of these products is higher. Therefore, the fourth observation also does not come as a surprise: prices are higher if complexity correlates with centrality (because more complex products are easier to find), but the effect is less pronounced than in the case of average product complexity (since stronger focus on complex products also comes with more competition).

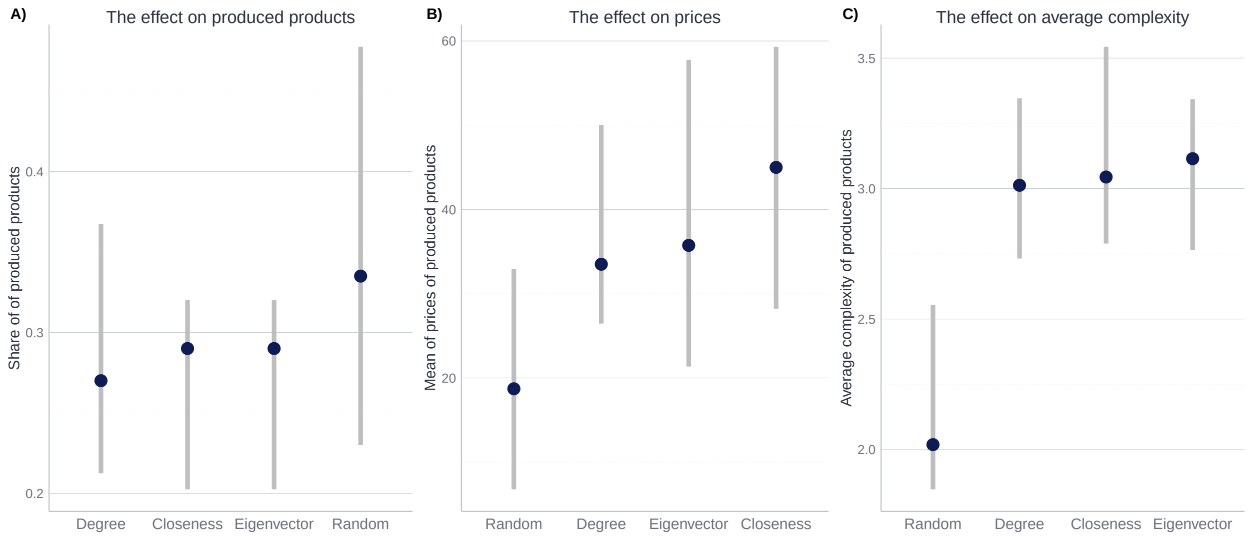

Figure 5: The effect of different allocation of product complexity. The figure shows median results after 250 steps of 50 iterations of the model, i.e. the situation during the final time step in figure 2. The other parameters are set to their baseline level described in table 5. The dots and whiskers represent the median result and the IQR, respectively. The topology of the product space is a Barabási-Albert graph.

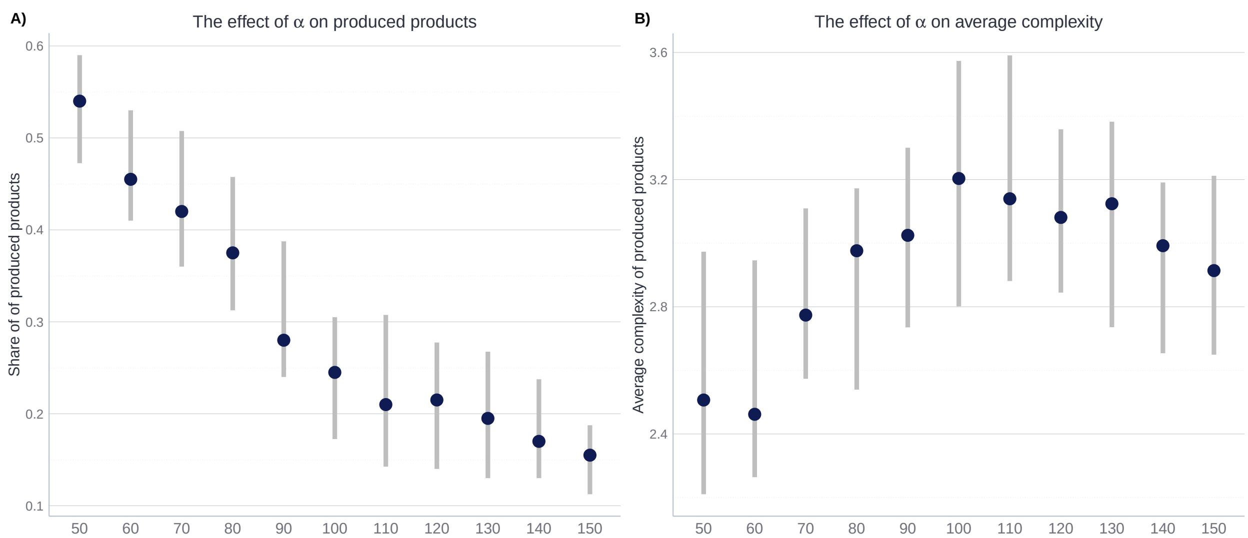

Figure 6: The effect of different values of α on the innovation dynamics. The figure shows median results after 250 steps of 50 iterations of the model, i.e. the situation during the final time step in figure 2. The other parameters are set to their baseline level described in table 5. The dots and whiskers represent the median result and the IQR, respectively. The topology of the product space is a Barabási-Albert graph.

4.3 Relevance of complexity for the product price

Finally, we consider the impact of the parameter α on the model results. As indicated in equation (1), this parameter controls the relevance of complexity for the prices of products. Figure 6 illustrates the nonlinear effect of α on the share of produced products and average product complexity:

First, one can observe a negative impact of α on the share of produced products. This relationship is particularly pronounced for $\alpha \leq 110$ and can be explained by (1) the fact that a lower α translates into lower profits and lower returns on investment, leading to less investment-friendly scenarios, which is why firms easier get stuck on products with low complexity, and, more importantly, (2) by the fact that complex products become relatively more attractive when complexity has a greater impact on prices Thus, if α grows, firms cease to produce simple products and focus on the more complex ones, which is why the share of products produced decreases and average complexity increases.

At the same time, this relative attractiveness gets compensated by the increase of competition that comes with a stronger concentration on complex products: if all firms desperately try to produce the same complex products, the competitive pressure on prices tends to outweigh the larger α. This is precisely what happens for $\alpha > 110$. Above this value, firms tend to evade the fierce competition for complex products by switching to less complex product or by not entering the markets for the most complex products at all. The result, as can be seen in figure 6, is a less pronounced reduction of the share of produced products and a slightly negative effect on average complexity for very large values of α as compare to medium to high values of α.

5 Discussion

Innovation and capability accumulation are important determinants of economic development. The empirical literature is very clear on this matter (e.g. Hidalgo et al, 2007; Hausmann et al, 2007; Dosi et al, 2019b). As has been shown in the concise literature review in section 2, the determinants of capability accumulation are manifold. With regard to the more theoretical literature we found that while various mechanisms have been formalized within microeconomic models, macroeconomic models largely consider innovation and capability accumulation processes in the context of *process innovation*. Although the empirical literature has stressed its relevance, *product innovation* has received less attention so far.

One reason for this might be that microeconomic models considering process innovation are relatively complex and pay attention to “too many” mechanisms and processes to be translated into a macroeconomic context. To advance the exchange between micro and macroeconomic modelling the goal in this paper was, then, to come up with a very simple ABM, which captures some key ideas from the empirical literature on product innovation – such as the ‘principle of relatedness’ (Hidalgo et al, 2018) – and to explore their theoretical implications. The focus so far was on the topological structure of the product space, the relationship between product complexity and centrality, as well as the relevance of complexity for price determination. And although the model has kept as simple as possible, the results are interesting and show the relevance of these abovementioned mechanisms for theoretical work.

In this context, the simplicity of the model is both an advantage and a drawback: the model design is obviously too simple to draw general conclusions. The absence of a household or government sector as well as the simplistic price formation process limit its applicability to real-world cases. But this is not what the model was designed for: it was meant as an illustration of how a module for product innovation processes for macroeconomic ABM could look like. Extending the model by adding a household and government sector, and then docking it into an existing macro ABM are logical next steps, but even in its current form the model has produced some interesting theoretical insights, which, however, also call for further investigation.

First, the structure of the product space as a measure for the relatedness of heterogeneous products has important implications and deserves further theoretical attention. The simulations show that even in a simple production economy in which the demand side is kept relatively primitive, the structure and distribution of product complexity *does* matter. Focusing exclusively on complete or random networks is insufficient if innovation dynamics are to be studies seriously within an evolutionary economic framework.

Second, the mechanisms affecting innovation dynamics are highly interdependent, even in the simplistic setting considered here. The relevance of product complexity for price formation, for example, is closely interdependent with the possibilities of firms to evade competition, which itself is again dependent on the topology of the product space. Such results on the interdependency and context-dependency of central mechanisms is consistent with the empirical literature: innovation scholars regularly stress that innovation and capability accumulation are very context-dependent processes, which depend on many socio-cultural specificities and interact with numerous other socio-economic processes (see the summary in Aistleitner et al, 2020). For the present model this means that although the results of the model and the provided interpretation in section 4 are mostly intuitive, a more serious assessment requires the model to be embedded into a more comprehensive macroeconomic framework. At the same time, the simplicity of the model also makes this seem realistic. Moreover the existing literature as well as the model above indicate that the agent-based modelling approach provides a viable framework to address this challenge since many mechanisms and their interdependencies can be considered. This optimistic interpretation is further strengthened by the possibility of approaching the challenge of modelling capability accumulation and product innovation in a modular manner: simple models, such as the present one, can be first developed and analysed in a simplified environment and later, once they have been discussed and compared against alternatives, integrated into an existing macroeconomic modelling framework.

So, in all, while the simplicity of the current models prevents it from providing an acceptable account of how product innovation actually takes place, it can be a viable first step towards an adequate consideration of these processes within a more comprehensive macroeconomic framework.

6 Conclusion

The paper introduced an ABM in which heterogeneous firms engage in various forms of capability accumulation and move on an artificial product space in the sense of Hidalgo et al (2007). Since we were mainly interested in the processes underlying product innovation – a topic that so far has received less attention than process innovation, despite being highly relevant for economic development (e.g. Hausmann et al, 2007; Felipe et al, 2012) – the focus of the model was exclusively on the production side of the economy and did not include the consumption or the government sector. Rather, the model was used to investigate the impact of various topological structures of the product space of our model on the innovation dynamics. The results confirm our initial intuition that once product heterogeneity is allowed and products are related to each other in non-trivial ways, innovation dynamics work very differently. While the empirical relevance of the 'principle of relatedness' in conjunction with product innovation processes has already been demonstrated (Hidalgo et al, 2007; Hausmann et al, 2007; Hidalgo et al, 2018), we hope to have stimulated the theoretical and model-based investigation of this subject.

That being said, the model implies some immediate avenues for future research, most of which relate directly to the second goal of our research, i.e. to bridge micro- and macroeconomic models of capability accumulation. An obvious next step is to use the present model as an innovation module within one of the existing agent-based macroeconomic models, as discussed in section 5. This not only allows for a more comprehensive analysis of the role of innovation for economic dynamics, but would also enable us to study how innovation dynamics interact with other relevant macroeconomic mechanisms. Second, by docking the model to an existing ABM one can can study how a model with homogeneous products and a focus process innovation – such as most of the existing ABM – reacts to the consideration of product heterogeneity. Such an integration would also allow for a closer theoretical exploration of the mechanisms that link product innovation and economic development, a link of which the empirical literature has highlighted the importance but not illuminated the underlying mechanisms (e.g. Hidalgo et al, 2007; Felipe et al, 2012; Tacchella et al, 2013).

An alternative course for future research is to remain within a more microeconomic context to explore and extend the model along other dimensions: first, one could explore the interaction among firms and the mechanisms underlying knowledge spillovers in greater depth. One possibility is to allow for closer collaboration among firms, such as joint research and innovation projects. Another option would be to add workers to the model and investigate the effect of knowledge spill-overs through worker migration, one of the main drivers of the principle of relatedness highlighted in the empirical literature (e.g. Neffke and Henning, 2013). Second, one could add the possibility of process innovation, such that firms not only can invest into the invention of new products, but also into the improvement of existing production processes. Having a model that features both different products as well as endogenous productivity dynamics would add much to the existing literature. Third, the consideration of different regions and interregional innovation dynamics have also been a prominent topic in the existing literature, albeit so far not in relation to a product space. Finally, and this concerns both a potential macro or micro variant of the mode, the investigation of different sets of innovation policies is an obvious subject of investigation for models in the spirit presented here. This is particularly relevant if one is interested in products that differ not only in terms of their complexity but also in the amount of labour required or energy emitted – such a setting would be particularly interesting to explore nowadays, when environmentally friendly structural change is on the top priority list of policy makers.

In all, we hope that the present model represents a small but first step in terms of both a closer integration of micro and macroeconomic investigations of innovation and capability accumulation, as well as in advancing the modelling of innovation dynamics in the presence of heterogeneous products.

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